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Monitoring start of season in Alaska with GLOBE, AVHRR, and MODIS data

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[1] This work evaluates whether continuity between Advanced Very High Resolution Radiometer (AVHRR) and Moderate Resolution Imaging Spectroradiometer (MODIS) normalized difference vegetation index (NDVI) is achievable for monitoring phenological changes in Alaska. This work also evaluates whether NDVI can detect changes in start of the growing season (SOS) in this region. Six quadratic regression models with NDVI as a function of accumulated growing degree days (AGDD) were developed from 2001 through 2004 AVHRR and MODIS NDVI data sets for urban, mixed, and forested land covers. Model parameters determined NDVI values for start of the observational period as well as peak and length of the growing season. NDVI values for start of the growing season were determined from the model equations and field observations of SOS made by GLOBE students and researchers at University of Alaska Fairbanks. AGDD was computed from daily air temperature. AVHRR and MODIS models were significantly different from one another with differences in the start of the observational season as well as start, peak, and length of the growing season. Furthermore, AGDD for SOS was significantly lower during the 1990s than the 1980s. NDVI values at SOS did not detect this change. There are limitations with using NDVI to monitor phenological changes in these regions because of snow, the large extent of conifers, and clouds, which restrict the composite period. In addition, differing processing and spectral characteristics restrict continuity between AVHRR and MODIS NDVI data sets.

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1. Introduction

[2] Since the late nineteenth century the global annual surface temperature has increased 0.6 ± 0.2°C with the largest temperature increases of the most recent warming (1976 to present) occurring over the midlatitude and high-latitude continents of the Northern Hemisphere [*Houghton et al.*, 2001]. Extent of annual snow cover also decreased during this time period over the Northern Hemisphere [*Groisman et al.*, 1994]. Alaska has been particularly sensitive to these changes. Mean annual temperatures in Alaska have increased by 3°C since the 1960s, the largest regional warming of any state in the United States [*Weller et al.*, 1999]. Furthermore, day-to-day temperature variability has decreased in the Northern Hemisphere [*Karl et al.*, 1995]. Globally, daily minimum temperature has increased at a faster rate than daily maximum temperature resulting in a decrease in the diurnal temperature range [*Karl et al.*, 1991; *Easterling et al.*, 1997]. In the United States, decreases have been strongest during autumn, but in Alaska there have been strong decreases throughout the year [*Karl et al.*, 1993]. In addition, a 400-year Arctic temperature record reconstructed from proxy data shows that the Arctic temperatures of the twentieth century are the highest of the past 400 years [*Overpeck et al.*, 1997].

[3] Additionally, satellite data have been used to monitor intrannual and interannual seasonal changes. Passive and active microwave have been effective at monitoring terrestrial snow cover and seasonal thawing in boreal regions [*Wissman*, 2000; *Derksen and Goodison*, 2003; *Kimball et al.*, 2004]. However, active microwave was not useful for detecting spring leaf flush in the Alaska boreal forest [*Verbyla*, 2001]. On the other hand, AVHRR NDVI from the past two decades showed an increase in NDVI at northern latitudes that many have been attributed to a longer growing season [*Myneni et al.*, 1997; *Tucker et al.*, 2001; *Zhou et al.*, 2001; *Shabanov et al.*, 2002; *Piao et al.*, 2006]. However, it is difficult to interpret these NDVI increases without field validation. NDVI, while commonly used to monitor vegetation, is only a surrogate measurement of plant photosynthetic activity so that the translation of the actual signal requires careful consideration [*Tucker*, 1979].

[4] A review of multitemporal remote sensing Arctic research from the past decade found the strongest signal of NDVI change corresponded with the expansion of the

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tundra shrub [*Stow et al.*, 2004]. The same increases in AVHRR NDVI, substantiated with corresponding field data and 50 years of repeat aerial photography, showed an increase in both range and size of tundra shrub in northern Alaska and the Pan-Arctic [*Sturm et al.*, 2001; *Tape et al.*, 2006]. In Arctic Alaska, field biomass data also corresponded to these NDVI changes [*Jia and Epstein*, 2003; *Walker et al.*, 2003].

[5] Furthermore, *Goetz et al.* [2005] found the boreal biome had undergone substantial changes during 1981 through 2003 that varied by vegetation type. Growing season length and photosynthetic activity of the tundra shrub showed temperature-related increases while interior forests showed a decrease in photosynthetic activity and no change in growing season length. They attributed these differences to a variety of influencing factors including fire disturbances, drought stress, and nutrient limitations on interior forest regions. Correspondingly, there was a two-fold increase in annual biomass burning during 1960 through 1990 in the North American boreal region [*Lavoue et al.*, 2000; *Andreae and Merlet*, 2001]. Fires are a significant source of aerosols and aerosols significantly impact NDVI values even after one-month compositing periods [*Vermote et al.*, 2002]. Additionally, boreal fire emissions in the upper Northern Hemisphere were higher during 2000 and 2003 than the early to mid-1990s [*Kasischke et al.*, 2005].

[6] Each of these NDVI studies does indicate, however, that northern latitudes, and especially boreal regions, exhibit strong evidence of change. In addition, various phenological field observations across Europe and North America show a corresponding lengthening of growing season, specifically an earlier start of season, since the 1950s [*Cayan et al.*, 2001; *Chmielewski and Rotzer*, 2001; *Fitter and Fitter*, 2002; *Menzel et al.*, 2006]. Therefore it is important to establish whether temporal NDVI can detect these earlier SOS dates since the spatial extent of satellite data allows for a larger area of study than field observations. Furthermore, observed shifts in earlier spring phenological events in both plant and animal responses have been attributed to anthropogenic climate change [*Root et al.*, 2003, 2005].

[7] Various approaches exist for estimating SOS from satellite data. Threshold-based approaches utilize either a set of NDVI values or a value calculated from minimum and maximum NDVI to determine start, end, and length of growing season [*Lloyd*, 1990; *Markon et al.*, 1995; *Suzuki et al.*, 2003]. Choosing the right threshold is essential because the threshold determines all metrics but having one threshold to represent all land cover types is problematic as minimum NDVI values differ by vegetation type (e.g. deciduous versus evergreen forest). Midpoint value techniques minimize these problems by using actual NDVI data to determine the threshold [*Kogan*, 1995; *White et al.*, 1997]. Inflection point methods detect time of transition from the temporal NDVI profile, and metrics are derived with time derivatives or logistic functions [*Moulin et al.*, 1997; *Zhang et al.*, 2003]. This method, while useful for biomes with multiple growing seasons, is problematic for regions with evergreen, snow effects, and slow rates of senescence [*Reed et al.*, 2003]. Curve derivative methods identify SOS from a rapid and sustained increase in the temporal curve with a delayed moving average [*Reed et al.*, 1994]. However, this method is difficult to implement in places like Alaska where year-round NDVI data are often unavailable because of excessive snow and clouds during winter months.

[8] Another approach is to model land surface phenology describing NDVI as a function of accumulated growing degree day (AGDD). *de Beurs and Henebry* [2004a, 2005] used a simple regression model to evaluate whether institutional changes in Kazakhstan had an effect on land surface phenology. They found that across different ecoregions their model explained a significant portion of NDVI variation and could be used to assess significant changes in land surface phenology. AVHRR NDVI data were used in both studies. However, they excluded specific AVHRR data sets, NOAA-7 and NOAA-11, because of documented sensor-related artifacts that could result in the detection of spurious trends [*de Beurs and Henebry*, 2004b]. Given such exclusions in single sensor studies, it is prudent to determine whether multisensor data sets are comparable. In a multisensor comparison of AVHRR, Landsat TM, and SPOT HRV data sets for a grassland site, *Goetz* [1997] found that once atmospherically corrected and properly calibrated, NDVI and surface radiant temperature data sets compared favorably among the three sensors.

[9] The objective of this research was to determine whether continuity between AVHRR and MODIS NDVI is achievable for monitoring phenological changes in boreal regions. Continuity between NDVI data is essential for long-term monitoring. MODIS NDVI offers enhanced processing and spectral characteristics to the longer AVHRR NDVI product, potentially making it more suitable for detecting small phenological changes. This work also evaluated whether NDVI, regardless of the sensor, has the needed sensitivity to detect changes in SOS for high northern latitudes. NDVI has been widely used to monitor phenological changes. However, much of this research does not have field validation. The high northern latitudes have experienced significant changes and it is important to establish whether NDVI is the proper tool to detect such changes in these regions.

2. Methods

2.1. Study Sites

[10] GLOBE students located in or near Fairbanks, Alaska, made SOS observations from 2001 through 2004 on *Betula* (Birch), *Populus* (Poplar), and *Salix* (Willow) at their school locations following established GLOBE plant phenology protocols (http://www.globe.gov). All three trees are native to Alaska [*Viereck and Little*, 1972]. Since 1999, GLOBE students from more than 200 schools around the world have made over 120,000 phenology measurements at their schools. Students in Alaska have collected nearly half of these measurements. This data set, largely untapped for scientific purposes, provides an exceptional means to validate satellite-derived phenology for boreal regions. SOS was defined when 50% of the buds for all sites of the same genus at one school had leafed out or burst. A statewide land cover map was used to determine land cover for each GLOBE site [*Fleming*, 1997]. Sites with similar locations, land cover classification, and temporal NDVI signatures were classified into three groups: forest, mixed, and urban.

Table 1. GLOBE Site Location and Information

School	Latitude, Longitude, Elevation	Land Cover, %	Group	Landform/Soils
Barnette	64.82°, 147.73° 150 m	Urban: 89%, MixForest: 11%	Urban (U)	Floodplains (LTER2) Cryofluvent
Joy	64.86°, 147.73° 144 m	Urban: 67%, Shrub: 33%	Mixed (M)	Floodplains (LTER2) Cryofluvent
Monroe	64.85°, 147.72° 143 m	Urban: 67%, Spruce: 33%	Mixed (M)	Floodplains (LTER2) Cryofluvent
Moosewood	64.88°, 147.79° 168 m	Mix Spruce and Shrub: 44%, MixForest: 33%, Urban: 22%	Forest (F)	Uplands (LTER1) Eutrocyept
North Pole	64.75°, 147.34° 167 m	Mix Spruce and Shrub: 89%, MixForest: 11%	Forest (F)	Uplands (LTER1) Eutrocyept
Ticasuk	64.83°, 147.52° 150 m	Mix Spruce and Shrub: 78%, MixForest: 22%	Forest (F)	Uplands (LTER1) Eutrocyept
West Valley	64.85°, 147.82° 122 m	Urban: 67%, MixForest: 22%, Shrub: 11%	Urban (U)	Floodplains (LTER2) cryofluvent

Table 1 shows location, land and soil information for the GLOBE sites.

[11] Additionally, green-up observations at the University of Alaska-Fairbanks (UAF) campus, made by two separate UAF research groups, were used. The first group (UAF1) made green-up observations from 1976 through 2004 and the second (UAF2) from 1988 through 1998 [*Thoman and Fathauer*, 1998]. Both groups made observations near the UAF campus on the Chena hillside, a site largely populated by birch [*Goldman*, 2000]. UAF SOS was defined by "a distinct green coloration in the forest" [*Thoman and Fathauer*, 1998].

2.2. Climate Products

[12] Meteorological data were obtained from NOAA weather stations at the Fairbanks International Airport for 1976 through 2004 (NOAA NCDC, http://www.ncdc.noaa.gov/oa/climate/research/ushcn/daily.html). Soil temperature data were obtained from Bonanza Creek Long-Term Ecological Research (LTER) program [*Miller*, 2004]. The Bonanza Creek site is located 20 km southwest of Fairbanks and has two weather stations collecting soil temperature (LTER1 and LTER2) since 1989. LTER1 is an upland site, elevation 355 m, with loess parent material. The soil is classified as a Fairbanks silt loam (coarse-silty, mixed, superactive typic eutrocryept). LTER2 is a floodplain site, elevation 130 m, located 150 m from the Tanana River, with alluvium parent material. The soil at this site is classified as a Salchaket (coarse-loamy, mixed, superactive, nonacid typic cryofluvent). To correspond with the appropriate LTER site, Fairbanks GLOBE sites were categorized into upland and floodplain groups based on their elevation and soil classification determined from the county soil survey [*Mulligan*, 2004].

[13] Annual accumulated growing degree days (AGDD) required for SOS were calculated from daily temperatures greater than 0°C from 1 March through time of observed SOS. The 1 March start date was chosen based on prior research by *Thoman and Fathauer* [1998] for Fairbanks, Alaska. AGDD for SOS were computed for 1976 through 2004 with daily maximum and mean air temperatures. AGDD for SOS were also computed for 1989 through 2004 with LTER1 and LTER2 10 cm soil temperatures. SOS was determined from the UAF1 field observations. Results from all four data sets were evaluated and validated with UAF2 and GLOBE SOS observations. The best data set was chosen to compute AGDD for the rest of the study.

Table 2. Observed Start of Season for Fairbanks by Date and Accumulated Growing Degree Days Shown in Parenthesis

	GLOBE				UAF1
Year	*Betula*	*Populus*	*Salix*	*Mean*	*Betula*
2001	5/15 (121)	5/17 (141)	5/18 (152)	5/17 (138)	5/18 (152)
2002	5/14 (90)	5/15 (102)	5/16 (113)	5/15 (102)	5/18 (137)
2003	5/5 (136)	4/28 (99)	4/28 (99)	4/30 (111)	5/6 (142)
2004	5/1 (108)	5/4 (137)	5/4 (137)	5/3 (127)	5/5 (145)

2.3. NDVI Products

[14] Maximum value, 14-day, 1-km resolution AVHRR NDVI composites for 2001 through 2004 and corresponding cloud mask files from the USGS Center for Earth Resources Observation and Science (USGS/EROS, Sioux Falls, South Dakota) were used. This data set includes data from AVHRR sensors on board NOAA-16 and 17 satellites and was atmospherically corrected for ozone, water vapor absorption, and Rayleigh scattering. In addition, all composites were cloud screened using an adaptation of the CLAVRR (Clouds from AVHRR) algorithm developed by *Stowe et al.* [1998]. It was not possible to use the 7-day 1-km AVHRR NDVI product because of excessive cloud cover. Maximum value biweekly 8-km resolution AVHRR NDVI composites for 1982 through May 2004 from the NASA Global Inventory Monitoring and Modeling Systems (GIMMS) group at NASA's Goddard Space Flight Center were also used [*Tucker et al.*, 2004]. This data set includes data from the AVHRR sensors on board the NOAA-7 through 17 satellites and provides improved results based on corrections for calibration, view geometry, volcanic aerosols, and other effects not related to actual vegetation change.

[15] In addition, MODIS/Terra Vegetation Indices 16-Day L3 1 km SIN Grid (MOD13A2) composites for 2001 through 2004 were used (LP DAAC, USGS/EROS, Sioux Falls, South Dakota). Cloud-contaminated composites

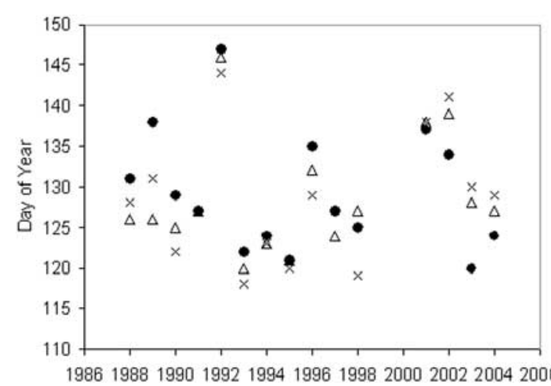

Figure 1. SOS computed from AGDD mean (open triangles) and maximum (crosses) air temperatures and UAF2 and GLOBE field observations (solid circles).

Table 3. Accumulated Growing Degree Days (AGDD) Required for Budburst From Budburst Observations and Air and Soil Temperatures

	Air Temperature (1976–2004)		Soil Temperature (1989–2004)	
AGDD	Maximum	Mean	LTER1	LTER2
Mean	391	153	28	24
SD	45	22	24	21
Range	303–478	116–201	0–68	0–70
CV	12%	14%	83%	88%

were identified with corresponding QA files from each data set. MODIS products were corrected for molecular scattering, water vapor, ozone absorption, and aerosols [*Vermote et al.*, 2002]. A constrained-view angle-maximum value composite (CV-MVC) algorithm to constrain strong angular variations encountered in the maximum value compositing (MVC) process was applied to MODIS data [*Huete et al.*, 2002]. The 8-day product was not used because too few unobstructed observations of the study sites were available from these composite periods.

[16] To ensure snow-free NDVI values, only composites from the observational season were used. The observational season began at the end of April for the AVHRR data sets and in the third week of April for the MODIS data set. The different start dates were the result of their different compositing periods. For all data sets, the observational season ran through the end of September. Fairbanks' 55-year climatic record showed mean monthly snow depths of 25, 0, 0, and 5 cm, respectively for April, May, September, and October, respectively [*Western Regional Climate Center*, 2007]. Furthermore, the MODIS QA files also indicated that there was snow all 4 years through the third week in April.

2.4. AVHRR and MODIS Models

[17] Corresponding 1-km AVHRR and MODIS NDVI data sets for 2001 through 2004 for Fairbanks were evaluated. MODIS data were stitched and reprojected to Albers Equal Area Conic of Alaska to match the AVHRR product. A 3 by 3 mean filter around each GLOBE site was applied to these biweekly NDVI composites. AVHRR composites were cloud screened using an adaptation of the CLAVRR algorithm developed by *Stowe et al.* [1998]. Cloud-contaminated composites were identified with corresponding QA files from each MODIS data set. Cloud-contaminated composites were replaced with mean values calculated from composite values preceding and following cloud-contaminated ones.

Table 5. The *p*-Values of the Simultaneous Tests on Coefficients for AVHRR and MODIS Models

Test	Urban	Mixed	Forest
T1 (all)	<0.0001	<0.0001	<0.0001
T2 (intercept)	<0.0001	<0.0001	<0.0001
T3 (linear)	<0.0001	0.8821	<0.0001
T4 (quadratic)	<0.0001	<0.0001	<0.0001

[18] Two statistical models, AVHRR and MODIS, were fitted for each group. The quadratic regression model from *de Beurs and Henebry* [2004a, 2004b, 2005] was used:

$$\mathrm{NDVI} = \alpha + \beta \mathrm{AGDD} + \gamma \mathrm{AGDD}^2 \tag{1}$$

NDVI is all AVHRR NDVI composite values from 2001 through 2004. AGDD is all the corresponding mean AGDD values from 2001 through 2004. Mean AGDD was computed from the daily AGDD values corresponding to each 14-day AVHRR NDVI composite period. The same was computed for each 16-day MODIS composite period for the MODIS models. The intercept (α) represents the NDVI value at the beginning of the observational season while the slope parameter (β) measures growing degree days required to reach NDVI peak and the quadratic parameter (γ) determines the shape of the curve and the length of the growing season [*de Beurs and Henebry*, 2004a, 2004b]. It is important to note that the intercept reflects the beginning of the observational season and not the start of the growing season. NDVI values for start of the growing season were determined from the model equations and field observations of SOS.

[19] The Mann-Whitney test was used to determine whether the AVHRR and MODIS NDVI and AGDD data sets were significantly different. The Mann-Whitney test was chosen because the data sets were nonnormal and had unequal sample sizes that were nonpaired. AVHRR data set had 44 images and a 14-day composite period while MODIS data set had 40 images and a 16-day composite period. The coefficient of determination (R^2), adjusted R^2 (R^2_{adj}), coefficient of variation (CV) and the root mean square error (RMSE) were calculated for each model. Simultaneous tests on coefficients were done to test for significant differences between AVHRR and MODIS model parameters [*Myers*, 1990]. Four tests (T1–T4) were performed on each group's model parameters. T1 tested all model parameters together while T2, T3, and T4, respectively, tested for individual differences between AVHRR and MODIS' intercept, linear coefficient, and quadratic coefficient, respectively. Additionally, the Mann-Whitney test was used to determine whether

Table 4. Models for AVHRR and MODIS 1-km NDVI Data Sets

Group	Data	Model	R^2_{adj}	RMSE
Urban	AVHRR	$\mathrm{NDVI} = 0.180 + 5.684\mathrm{E}^{-4}\mathrm{AGDD} - 2.383\mathrm{E}^{-7}\mathrm{AGDD}^2$	0.78	0.052
Urban	MODIS	$\mathrm{NDVI} = 0.240 + 5.137\mathrm{E}^{-4}\mathrm{AGDD} - 2.077\mathrm{E}^{-7}\mathrm{AGDD}^2$	0.80	0.048
Mixed	AVHRR	$\mathrm{NDVI} = 0.251 + 5.263\mathrm{E}^{-4}\mathrm{AGDD} - 2.192\mathrm{E}^{-7}\mathrm{AGDD}^2$	0.73	0.054
Mixed	MODIS	$\mathrm{NDVI} = 0.290 + 5.214\mathrm{E}^{-4}\mathrm{AGDD} - 2.031\mathrm{E}^{-7}\mathrm{AGDD}^2$	0.83	0.046
Forest	AVHRR	$\mathrm{NDVI} = 0.288 + 6.509\mathrm{E}^{-4}\mathrm{AGDD} - 2.891\mathrm{E}^{-7}\mathrm{AGDD}^2$	0.71	0.068
Forest	MODIS	$\mathrm{NDVI} = 0.402 + 6.087\mathrm{E}^{-4}\mathrm{AGDD} - 2.479\mathrm{E}^{-7}\mathrm{AGDD}^2$	0.77	0.060

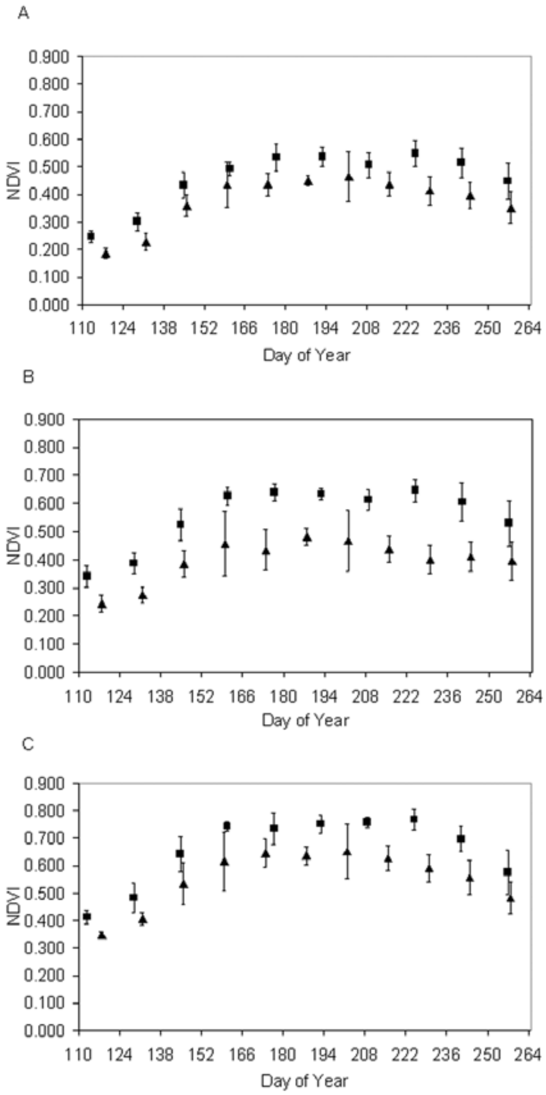

Figure 2. Mean biweekly AVHRR (solid triangles) and MODIS (solid squares) NDVI with seasonal trajectories at start date of each composite period for (a) urban, (b) mixed, and (c) forest groups.

each sensor's NDVI and AGDD values at SOS were significantly different from one another.

2.5. SOS Test

[20] Biweekly NDVI composites from 1982 through 2003 were extracted from the 8-km AVHRR data set for each GLOBE site. Several sites were in the same 8-km pixel because of their proximity to one another and as a result the sites were classified into two groups. The first group was a combination of urban, shrub and forest land cover similar to the mixed group from Table 1. The second group was a combination of spruce and mixed forest land cover similar to forest group from Table 1. As discussed above, end of April through September composites were used to ensure snow-free NDVI values.

[21] Annual SOS for 1982 through 2003 was determined from the UAF1 observations. These field observations were converted to AGDD and composited to the same biweekly time period as the 8-km AVHRR data set and mean AGDD for the SOS composite period was used. These AGDD values were applied to the AVHRR and MODIS models to compute NDVI at SOS for each year. These results were compared to NDVI values at SOS from the 8-km AVHRR data set. The Wilcoxon signed rank test was used to determine whether NDVI values from the 1-km AVHRR and MODIS models were significantly different than the 8-km NDVI values. The Wilcoxon signed rank test was chosen because the data sets were nonnormal but the samples were paired.

3. Results

[22] Overall, field observations made by GLOBE students showed similar annual SOS dates by species (Table 2). However, in 2003 *Betula* budburst was one week later than the other tree species. *Linkosalo* [1999] also found a similar uniformity of phenological events between different species in Finnish forests. Overall, GLOBE students' observations were earlier by four days or less (14 to 35 AGDD) than the UAF1 researchers' observations. In Fairbanks, *Thoman and Fathauer* [1998] found green-up began on lower elevations of south facing hillsides, spreading quickly down valley floors, and moving more slowly up higher elevation hillsides. Most of the GLOBE sites were located in the valley whereas UAF1, and UAF2, sites were located on Chena Hillside near the UAF campus. UAF2 only made observations from 1988 through 1998. Overall, their observations

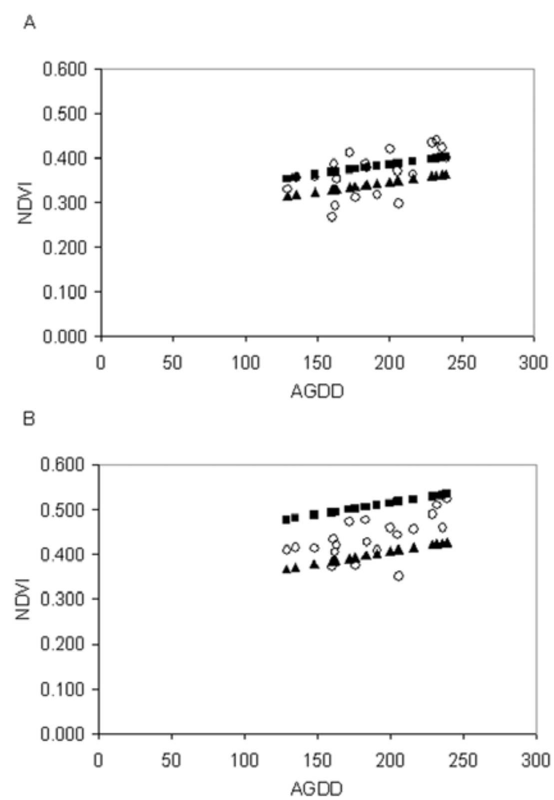

Figure 3. NDVI and AGDD at SOS for 1-km AVHRR (solid triangles), 8-km AVHRR (open circles) and MODIS (solid squares) NDVI for (a) Group 1/Mixed and (b) Group 2/Forest.

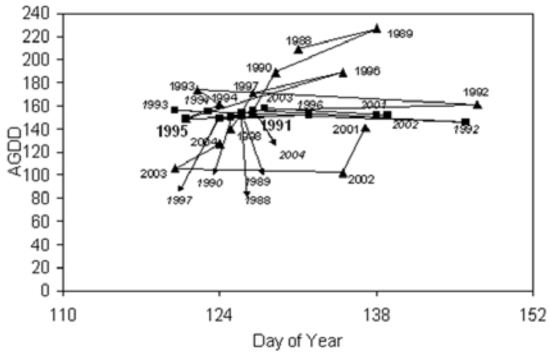

Figure 4. AGDD for observed SOS (solid triangles) and predicted SOS (solid squares) by year. Regular font indicates observed SOS, and italic indicates predicted SOS. Bold indicates observed and predicted SOS have same DOY and AGDD for that particular year.

were later by four days or less than the UAF1 observations.

[23] Table 3 shows mean, standard deviation, range, and coefficient of variation (CV) for each of the four AGDD data sets. The air temperature data sets resulted in the lowest coefficient of variations. Figure 1 shows actual and computed SOS for Fairbanks from the two air temperature data sets. The soil temperature data sets were not used to predict SOS because of their high standard deviations and coefficients of variations. AGDD was computed from daily mean air temperature because overall it predicted SOS best. AGDD threshold was 153 with values ranging from 116 to 201.

[24] The 1-km AVHRR and corresponding MODIS NDVI curves showed similar seasonal temporal patterns for all three sites (Figure 2). However, MODIS values were higher and remained higher throughout the season. MODIS data also had less interannual variability during June through August, the height of the growing season. NDVI data sets were significantly different (α = 0.05) from one another while their corresponding AGDD data sets were not, indicating differences were related to sensor type rather than composite periods.

[25] The AVHRR and MODIS quadratic regression models fit well for the urban, mixed, and forest groups. MODIS models performed better than their corresponding AVHRR models for all three groups. R^2_{adj} ranged from 0.71 to 0.83 with an average of 0.73 and 0.80 for the AVHRR and NDVI data, respectively (Table 4). The simultaneous tests on coefficients showed that the MODIS and corresponding AVHRR models were significantly different (α = 0.05) for each of the three groups. Additionally, with the exception of the linear coefficient for the mixed group, the AVHRR coefficients and intercept were significantly different from their corresponding MODIS coefficients and intercept (Table 5). Table 6 shows the computed NDVI values at SOS from the NDVI models and the AGDD threshold. The MODIS NDVI values were significantly higher (α = 0.05) than the AVHRR values for all three groups.

[26] Figure 3 show the computed and actual NDVI values at SOS for the mixed and forest groups. MODIS SOS values were significantly higher (α = 0.05) than the 1 and 8 km AVHRR SOS values for Group 2 (forest). MODIS SOS values were not significantly different (α = 0.05) from the 8-km AVHRR SOS values for Group 1 (mixed). However, they were significantly different from the 1-km AVHRR SOS values (Tables 7 and 8). Additionally, UAF1 SOS field observations for the 1980s and 1990s showed significant decadal differences (α = 0.05) between 1980s and 1990s AGDD values (Table 9). The 1990s had lower AGDD values (123–177) than the 1980s (146–201). All three NDVI data sets showed interannual variation in NDVI values at SOS, but they did not detect significant decadal differences between 1980s and 1990s values as the AGDD data did (Tables 7 and 8).

[27] Figure 4 shows annual AGDD, computed from mean air temperature, for observed and predicted SOS. No trend in AGDD was shown in observed SOS and the slope was not significantly different from 0. There was interannual variation in both DOY and AGDD during this time period with no discernible correlation between DOY and AGDD. The range of DOY and AGDD were 120 to 147 and 102 to 227, respectively. On the other hand, AGDD at SOS was relatively consistent across a range of DOY dates for predicted SOS. AGDD were 146 to 158 while DOY ranged from 120 to 146.

4. Discussion

[28] Results indicate that there are significant limitations in continuity between AVHRR and MODIS NDVI data sets, which make long-term SOS monitoring problematic for environments like Fairbanks, Alaska. Ideally, a methodology for determining SOS from NDVI data should be developed with AVHRR NDVI, and then applied to MODIS NDVI. AVHRR NDVI has a significantly longer time series, which strengthens the validation process. MODIS NDVI has enhanced processing and spectral characteristics, which make it more suitable for detecting small changes in SOS. The wider spectral NIR band of AVHRR is more sensitive to water vapor and dampens NDVI values [*Chilar et al.*, 2001]. Furthermore, there is an increased chlorophyll sensitivity of the MODIS red-band [*Gitelson and Kaufman*, 1998; *Huete et al.*, 2002].

[29] At the start of each observational season, MODIS values were higher than AVHRR and remained higher throughout the season for all three land cover groups. Each of the model parameters were tested individually to ascertain whether the models were different solely because of the

Table 6. NDVI at SOS Calculated From AVHRR and MODIS Models and AGDD Threshold and Range

	Urban		Mixed		Forest	
NDVI	AVHRR	MODIS	AVHRR	MODIS	AVHRR	MODIS
Minimum	0.243	0.297	0.309	0.348	0.360	0.469
Mean	0.261	0.314	0.326	0.365	0.381	0.489
Maximum	0.285	0.335	0.348	0.387	0.407	0.514

Table 7. NDVI at SOS for the 1980s and 1990s for Group 1 Mixed Landcover

	AVHRR (8 km)		AVHRR (1 km)[a]		MODIS (1 km)	
Group 1 (Mixed)	1980s	1990s	1980s	1990s	1980s	1990s
Minimum	0.313	0.294	0.324	0.315	0.363	0.354
Mean	0.377	0.366	0.343	0.336	0.382	0.375
Maximum	0.436	0.422	0.363	0.364	0.402	0.403

[a]Significantly different at 0.05 level.

intercept parameter, which represented the initial value for the observational season. If the only significant difference between the models was the intercept parameter then adding a designated offset to the AVHRR values would make the data sets continuous. However, the models had significantly different intercepts as well as linear and quadratic coefficients. The models also produced significantly different NDVI values for SOS. The coefficients affect peak, length, and overall shape of each curve which ultimately result in two very different NDVI curves. Such differences make long-term monitoring with both data sets difficult.

[30] *Huete et al.* [2002] and *Brown et al.* [2006] showed similar findings to this work when comparing AVHRR and MODIS NDVI time series data. *Huete et al.* [2002] compared 1-km MODIS NDVI biweekly composites with corresponding AVHRR NDVI biweekly composites across various North American sites for the 2000–2001 season. *Brown et al.* [2006] compared 500-m MODIS NDVI biweekly composites with 8-km AVHRR GIMMS NDVI biweekly composites for 2000 through 2004 across various sites throughout the world. *Brown et al.* [2006] attributed MODIS' higher NDVI values to the sensors' different processing and spectral characteristics.

[31] In addition to the greater sensitivity of MODIS' red and NIR bands, these differences also restricted impacts from clouds, aerosols, and water vapor. Aerosols significantly impact NDVI values and their effects remain in data even after one-month compositing periods [*Vermote et al.*, 2002]. *Huete et al.* [2002] attributed sensor differences to these same factors in addition to MODIS' improved compositing method (CV-MVC). CV-MVC reduces spatial and temporal discontinuities that result from maximum value compositing [*Goward et al.*, 1991; *Huete et al.*, 2002]. The AVHRR water vapor effects did not apply for this study because a validated water vapor correction was applied to all, past and subsequent, 1-km AVHRR time series data as of 2001 [*DeFelice et al.*, 2003]. Nonetheless, compositing and aerosols factors did apply for this study. AVHRR NDVI data were composited with 14-day maximum values whereas MODIS data were composited with 16-day constrained view angle maximum values. Moreover, boreal fire emissions in the high Northern Hemisphere were higher during 2000 and 2003 than the early to mid-1990s [*Kasischke et al.*, 2005]. *Kasischke et al.*'s [2005] findings are especially relevant given that NDVI data from 2001 through 2004 were used in this study.

[32] Apart from continuity issues, the advancement of SOS that has been repeatedly observed and documented across Europe has averaged 2.5 days per decade [*Menzel et al.*, 2006]. Therefore in order to effectively monitor long-term seasonal changes, NDVI, regardless of sensor type, must be sensitive enough to detect such changes. Furthermore, the late 1970s through the mid 1990s have been classified as a warm Pacific Decadal Oscillation (PDO) phase, which coincides with dry periods for interior Alaska and warm winter and spring temperatures for northwestern North America [*Minobe*, 2000; *Mantua and Hare*, 2002]. Additionally, the 1990s was the warmest decade in the northern Pacific region since the 1850s [*Storm et al.*, 2004]. Theoretically, warmer spring temperatures would result in an earlier budburst and SOS. However, significantly drier conditions could delay budburst.

[33] In the scope of this current research it is difficult to ascertain whether the SOS changes detected in the 1980s and 1990s AGDD values resulted from the Pacific Decadal Oscillation or a combination of factors. The data show that the 1990s had significantly fewer AGDD at budburst (Table 9). But such a shift could have resulted from any number of climatic and environmental factors, local as well as larger ones such as the PDO. The results showed that the AVHRR and MODIS data sets did not detect the decadal changes in SOS (Tables 7 and 8). Furthermore, each NDVI data set was significantly different for the forest group (Table 8). MODIS values were consistently higher and the 1-km AVHRR values consistently lower than the 8-km AVHRR values. The MODIS values were similar to the 8-km AVHRR values for the mixed group, but the 1-km AVHRR data sets were significantly different and lower than the other data sets (Table 7).

[34] Nonetheless the data does indicate a corresponding degree of sensitivity is required from the NDVI data sets for monitoring SOS. Figure 4 shows that biweekly NDVI

Table 8. NDVI at SOS for the 1980s and 1990s for Group 2 Forest Landcover

	AVHRR (8 km)[a]		AVHRR (1 km)[a]		MODIS (1 km)[a]	
Group 2 (Forest)	1980s	1990s	1980s	1990s	1980s	1990s
Minimum	0.376	0.405	0.378	0.367	0.487	0.476
Mean	0.439	0.443	0.402	0.392	0.509	0.500
Maximum	0.489	0.525	0.426	0.427	0.532	0.533

[a]Significantly different at 0.05 level.

Table 9. AGDD at SOS for the 1980s and 1990s

AGDD	1980s[a]	1990s[a]
Minimum	146	123
Mean	174	148
Maximum	201	177

[a]Significantly different at 0.05 level.

compositing periods have limited capabilities for detecting interannual variability in SOS. *Fisher and Mustard* [2007] found phenological variability on the ground could be observed from satellites with spectral mixture analysis, but the observational metric had to have compatible meaning. However, they also found interannual phenological variability recorded by satellites may be dampened by 40 to 50% compared to those recorded by ground-based phenological observations. Furthermore, *Fisher et al.* [2007] found satellite phenology derived from a spectral mixture analysis (SMA) responded to opening of leaves whereas phenology derived from NDVI was highly dependent on the spectral contrast of the red to near infrared transition. They noted that since soil and litter have a slightly higher NDVI than snow, soil and litter may complicate the NDVI signal at SOS, which may result in an earlier onset prediction. At high latitudes ground cover, which is nearly continuous under sparse canopies, would also affect the NDVI signal.

[35] At the same time, one must be prudent with AGDD. Figure 4 also indicates that the AGDD model was a poor predictor of SOS. It did not capture the interannual variability of AGDD at SOS and DOY predictions more closely corresponded to observations than AGDD. *Fisher et al.* [2007] found that an AGDD model showed little improvement from an DOY model in predicting onset of spring in deciduous forests throughout New England. Furthermore, they found that satellite observations directly linked to climate could not adequately explain variability seen in temperate deciduous forests. They also found that forests in different regions did not respond similarly to climate variability as many ground-based phenological studies suggest. However, it should be noted that their work focused on detecting microscale variations in phenology metrics and in such cases dampening effects are due, in part, to discrepancies in observational scales.

[36] In Alaska, detecting SOS from NDVI is limited by late spring snow and evergreen vegetation. MODIS QA files indicated there was snow through the third week of April during 2001 through 2004. Correspondingly, the most rapid increase in MODIS NDVI occurred from the 7–22 April composite to the 23 April to 8 May composite period (data not shown). As noted previously, the start of the observation period differs from the start of the growing season. The observation period began the third week of April for MODIS data set, and end of April for the AVHRR data sets while field observations from GLOBE students and UAF1 researchers showed SOS occurred during the first two weeks in May for all four years. As previously mentioned, Fairbanks' climatic record showed snow depths averaging 25 cm for April while May had no snow. Therefore, we can assume that NDVI was detecting spring leaf flush rather than the melting of snow, which would also increase NDVI values. However, *Fisher et al.* [2007] found satellite phenology derived from a spectral mixture analysis (SMA) responded to opening of leaves whereas phenology derived from NDVI was highly dependent on the spectral contrast of the red to near infrared transition. They noted that since soil and litter have a slightly higher NDVI than snow, soil and litter may complicate the NDVI signal at SOS which may result in an earlier onset prediction.

[37] *Delbart et al.* [2005, 2006] also found that snow restricted the efficacy of monitoring SOS with NDVI in Siberia. They showed that normalized difference water index (NDWI), similar to NDVI but calculated from the short-wave infrared band instead of the red band, differentiated between snowmelt and green up and was more efficient at estimating SOS. However, this method had limitations in forests dominated by conifers which were what the forested sites in this study predominately were (Table 1).

[38] Effects of clouds, and subsequently composite length, also limit NDVI as a monitoring tool for SOS in boreal regions such as Alaska. Compositing, while necessary for mitigating cloud effects, restricts the sensitivity of NDVI to detect phenological changes. Furthermore, *Kasischke and French* [1997] found that clouds and atmospheric haze had significant effects on the AVHRR NDVI signature for boreal forests in Alaska even after compositing procedures were applied to the NDVI data. Short (<7 days) composite periods are required to detect such changes as above. However, weekly AVHRR and MODIS composites could not be used in this study because of high cloud levels. *Ahl et al.* [2006] also found composites of less than 7 days were required to capture the rapid green-up of a deciduous broadleaf forest in northern Wisconsin but 4 out of 5 days the daily MODIS products could not be used due to clouds.

5. Conclusions

[39] This research shows differing processing and spectral characteristics of the AVHRR and MODIS sensors restrict continuity between the NDVI data sets for Fairbanks, Alaska. The AVHRR and MODIS regression models resulted in significantly different NDVI curves and subsequently different start, peak, and length of growing seasons in all three land cover groups. Such differences make long-term SOS monitoring with a combined AVHRR and MODIS data set problematic.

[40] Additionally, the results from this study coupled with the well documented advancement of the time of spring shown in the literature, show that a more sensitive predictor than NDVI is needed to monitor changes in start of growing season. AGDD SOS values were significantly lower during the 1990s than the 1980s. However, the AVHRR and MODIS regression models as well as the 8-km AVHRR data set did not detect this decadal shift. NDVI, while useful for its spatial coverage, has limitations in boreal regions due to snow, the large extent of conifers, and clouds, which restrict the composite period. Cloudy conditions found in these regions prohibit use of a composite period shorter than 14 days and a biweekly composite period has limited capabilities for detecting gradual changes in SOS.

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References

Ahl, D., S. Gower, S. Burrows, N. Shabanov, R. Myeneni, and Y. Knyazikhin (2006), Monitoring spring canopy phenology of a deciduous broadleaf forest using MODIS, *Remote Sens. Environ.*, *104*, 88–95.

Andreae, M., and P. Merlet (2001), Emission of trace gases and aerosols from biomass burning, *Global Biogeochem. Cycles*, *15*, 955–966.

Brown, M., J. Pinzon, K. Didan, J. Morisette, and C. Tucker (2006), Evaluation of the consistency of long-term NDVI time series derived from AVHRR, SPOT-vegetation, SeaWIFS, MODIS and LandSAT ETM+ sensors, *IEEE Trans. Geosci. Remote Sens.*, *44*, 1787–1793.

Cayan, D., S. Kammerdiener, M. Dettinger, J. Caprio, and D. Peterson (2001), Changes in the onset of spring in the western United States, *Bull. Am. Meteorol. Soc.*, *82*, 399–415.

Chilar, J., I. Tcherednichchenko, R. Latifovic, Z. Li, and J. Chen (2001), Impact of variable atmospheric water vapor content on AVHRR data corrections over land, *IEEE Trans. Geosci. Remote Sens.*, *39*, 173–180.

Chmielewski, F., and T. Rotzer (2001), Response of tree phenology to climate change across Europe, *Agric. For. Meteorol.*, *108*, 101–112.

de Beurs, K., and G. Henebry (2004a), Land surface phenology, climatic variation, and institutional change: Analyzing agricultural land cover change in Kazakhstan, *Remote Sens. Environ.*, *49*, 497–509.

de Beurs, K., and G. Henebry (2004b), Trend analysis of the Pathfinder AVHRR Land (PAL) NDVI data for the deserts of Central Asia, *Geosci. Remote Sens. Lett.*, *1*, 282–286.

de Beurs, K., and G. Henebry (2005), A statistical framework for the analysis of long image time series, *Int. J. Remote Sens.*, *26*, 1551–1573.

DeFelice, T., D. Lloyd, D. Meyer, T. Baltzer, and P. Piraino (2003), Water vapour correction of the daily 1 km AVHRR global land data set: Part I – Validation and use of the water vapour input field, *Int. J. Remote Sens.*, *24*, 2365–2375.

Delbart, N., L. Kergoat, T. Le Toan, J. Lhermitte, and G. Picard (2005), Determination of phenological dates in boreal regions using normalized difference water index, *Remote Sens. Environ.*, *97*, 26–38.

Delbart, N., T. Le Toan, L. Kergoat, and V. Fedotova (2006), Remote sensing of spring phenology in boreal regions: A free of snow-effect methods using NOAA_AVHRR and SPOT_VGT data (1982–2004), *Remote Sens. Environ.*, *101*, 52–62.

Derksen, C., and W. Goodison (2003), A comparison of 18 winter seasons of in situ and passive microwave-derived snow water equivalent estimates in western Canada, *Remote Sens. Environ.*, *88*, 271–282.

Easterling, D., et al. (1997), Maximum and minimum temperature trends for the globe, *Science*, *277*, 364–367.

Fisher, J., and J. Mustard (2007), Cross-scalar satellite phenology from ground, Landsat, and MODIS data, *Remote Sens. Environ.*, *109*, 261–273.

Fisher, J., A. Richardson, and J. Mustard (2007), Phenology model from surface meteorology does not capture satellite-based green-up estimations, *Global Change Biol.*, *13*, 707–721.

Fitter, A., and R. Fitter (2002), Rapid changes in flowering time in British plants, *Science*, *296*, 1689–1691.

Fleming, M. (1997), A statewide vegetation map of Alaska using a phenological classification of AVHRR data, in *Proceedings of the Second Circumpolar Arctic Vegetation Mapping Workshop and the CAVM-North American Workshop*, edited by D. A. Walker and A. C. Lillie, 62 pp., Anchorage, Alaska.

Gitelson, A., and Y. Kaufman (1998), MODIS NDVI optimization to fit the AVHRR data series – spectral considerations, *Remote Sens. Environ.*, *66*, 343–350.

Goetz, S. (1997), Multisensor analysis of NDVI, surface temperature and biophysical variables at a mixed grassland site, *Int. J. Remote Sens.*, *18*, 71–94.

Goetz, S., A. Bunn, G. Fiske, and R. Houghton (2005), Satellite-observed photosynthetic trends across boreal North America associated with climate and fire disturbance, *Proc. Natl. Acad. Sci.*, *102*, 13,521–13,525.

Goldman, H. (2000), Estimation of growing season length in northern Alaska with AVHRR NDVI bi-weekly satellite data, M.S. thesis, Univ. of Alaska-Fairbanks, Fairbanks.

Goward, S., B. Markham, D. Dye, W. Dulaney, and J. Yang (1991), Normalized difference vegetation index measurements from the Advanced Very High Resolution Radiometer, *Remote Sens. Environ.*, *35*, 257–277.

Groisman, P., K. Thomas, and R. Knight (1994), Observed impact of snow cover on the heat balance and the rise of continental spring temperatures, *Science*, *263*, 198–200.

Houghton, J., et al. (Ed.) (2001), *Climate Change 2001: The Scientific Basis*, 881 pp., Cambridge Univ. Press, Cambridge, UK.

Huete, A., K. Didan, T. Miura, E. Rodriguez, X. Gao, and L. Ferreira (2002), Overview of the radiometric and biophysical performance of the MODIS vegetation indices, *Remote Sens. Environ.*, *83*, 195–213.

Jia, G., and H. Epstein (2003), Greening of Arctic Alaska, 1981–2001, *Geophys. Res. Lett.*, *30*(20), 2067, doi:10.1029/2003GL018268.

Karl, T., et al. (1991), Global warming: Evidence for asymmetric diurnal temperature change, *Geophys. Res. Lett.*, *18*, 2253–2256.

Karl, T., et al. (1993), Asymmetric trends of daily maximum and minimum temperature, *Bull. Am. Meteorol. Soc.*, *74*, 1007–1023.

Karl, T., R. Knight, and N. Plummer (1995), Trends in high-frequency climate variability in the twentieth century, *Nature*, *377*, 217–2001.

Kasischke, E., and N. French (1997), Constraints on using AVHRR composite index imagery to study patterns of vegetation cover in boreal forests, *Int. J. Remote Sens.*, *18*, 2403–2426.

Kasischke, E., et al. (2005), Influences of boreal fire emissions on Northern Hemisphere atmospheric carbon and carbon, *Global Biogeochem. Cycles*, *19*, GB1012, doi:10.1029/2004GB002300.

Kimball, J., K. McDonald, S. Frokling, and S. Running (2004), Radar remote sensing of the spring thaw transition across a boreal landscape, *Remote Sens. Environ.*, *89*, 163–175.

Kogan, F. (1995), Droughts of the late 1980s in the United States as derived from NOAA polar-orbiting satellite data, *Bull. Am. Meteorol. Soc.*, *76*, 665–668.

Lavoue, D., C. Liousse, H. Cachier, B. Stocks, and J. Goldammer (2000), Modeling of carbonaceous particles emitted by boreal and temperate wildfires at northern latitudes, *J. Geophys. Res.*, *105*, 26,871–26,890.

Linkosalo, T. (1999), Regularities and patterns in the spring phenology of some boreal trees, *Silva Fennica*, *33*, 237–245.

Lloyd, D. (1990), A phenological classification of terrestrial vegetation cover using shortwave vegetation index imagery, *Int. J. Remote Sens.*, *11*, 2269–2279.

Mantua, N., and S. Hare (2002), The Pacific Decadal Oscillation, *J. Oceanogr.*, *58*, 35–44.

Markon, C., M. Fleming, and E. Binnian (1995), Characteristics of vegetation phenology over the Alaskan landscape using AVHRR time-series data, *Polar Rec.*, *31*, 179–190.

Menzel, A., et al. (2006), European phenological response to climate change matches the warming pattern, *Global Change Biol.*, *12*, 1969–1976.

Miller, S. (2004), Soil temperature at LTER weather stations: Daily and hourly data, E Fairbanks, AK, *Bonanza Creek LTER Database, BNZD00098:90*. (Available at http://www.lter.uaf.edu/data_catalog_detail.cfm?dataset_id=90)

Minobe, S. (2000), Spatial-temporal structure of the pentadecadal variability over the North Pacific, *Prog. Oceanogr.*, *47*, 381–408.

Moulin, S., L. Kergoat, N. Viovy, and G. Dedieu (1997), Global-scale assessment of vegetation phenology using NOAA/AVHRR satellite measurements, *J. Clim.*, *10*, 1154–1170.

Mulligan, D. (2004), Soil survey of greater Fairbanks area, Alaska, Nat. Resour. Conserv. Serv., U.S. Dep. of Agric., Washington, D. C.

Myers, R. (1990), *Classic and Modern Regression With Applications*, 2nd ed., 488 pp., PWS-KENT, Boston, Mass.

Myneni, R., C. Keeling, C. Tucker, G. Asrar, and R. Nemani (1997), Increased plant growth in the northern high latitudes from 1981–1991, *Nature*, *386*, 698–702.

Overpeck, J., et al. (1997), Arctic environmental change of the last four centuries, *Science*, *278*, 1251–1256.

Piao, S., J. Fang, L. Zhou, P. Ciais, and B. Zhu (2006), Variations in satellite-derived phenology in China's temperate vegetation, *Global Change Biol.*, *12*, 1–14.

Reed, B., J. Brown, D. VanderZee, T. Loveland, J. Merchant, and D. Ohlen (1994), Measuring phenological variability from satellite imagery, *J. Vegetation Sci.*, *5*, 703–714.

Reed, B., M. White, and J. Brown (2003), Remote sensing phenology, in *Phenology: An Integrative Environmental Science*, edited by M. Schwartz, pp. 365–381, Kluwer Acad., Dordecht, Netherlands.

Root, T., J. Price, K. Hall, S. Schneiders, C. Rosenzweig, and J. Pounds (2003), Fingerprints of global warming on wild animals and plants, *Nature*, *421*, 57–60.

Root, T., D. MacMynowski, M. Mastrandrea, and S. Schneider (2005), Human-modified temperatures induce species changes: Joint attribution, *Proc. Natl. Acad. Sci.*, *102*, 7465–7469.

Shabanov, N., L. Zhou, Y. Knyazikhin, R. Myneni, and C. Tucker (2002), Analysis of interannual changes in northern vegetation activity observed in AVHRR data from 1981 to 1994, *IEEE Trans. Geosci. Remote Sens.*, *40*, 115–130.

Storm, A., R. Francis, N. Mantua, E. Miles, and D. Peterson (2004), North Pacific climate recorded in growth rings of geoduck clams: A new tool for paleoenvironmental reconstruction, *Geophys. Res. Lett.*, *31*, L06206, doi:10.1029/2004GL019440.

Stow, D., et al. (2004), Remote sensing of vegetation and land-cover change in Artic Tundra ecosystems, *Remote Sens. Environ.*, *89*, 281–308.

Stowe, L., P. Davis, and E. McClain (1998), Scientific basis and initial evaluation of the CLAVR-1 Global Clear/Cloud Classification Algorithm for the Advanced Very High Resolution Radiometer, *J. Atmos. Oceanic Technol.*, *16*, 656–681.

Sturm, M., C. Racine, and K. Tape (2001), Increasing shrub abundance in the Arctic, *Nature*, *411*, 546–547.

Suzuki, R., T. Nomaki, and T. Yasunari (2003), West-east contrast of phenology and climate in northern Asia revealed using a remotely sensed vegetation index, *Int. J. Biometeorol.*, *47*, 126–138.

Tape, K., M. Sturm, and C. Racine (2006), The expansion for shrub expansion in northern Alaska and the Pan-Arctic, *Global Change Biol.*, *12*, 1–17.

Thoman, R., and T. Fathauer (1998), An investigation into estimating green-up dates around Fairbanks Alaska using thermal indices, Natl. Weather Serv.

Tucker, C. J. (1979), Red and photographic infrared linear combinations for monitoring vegetation, *Remote Sens. Environ.*, *8*, 127–150.

Tucker, C. J., D. A. Slayback, J. E. Pinzon, S. O. Los, R. B. Myneni, and M. G. Taylor (2001), Higher northern latitude normalized difference vegetation index and growing season trends from 1982 to 1999, *Int. J. Biometeorol.*, *45*, 184–190.

Tucker, C., J. Pinzon, and M. Brown (2004), Global Inventory Modeling and Mapping Studies (GIMMS) satellite drift corrected and NOAA-16 incorporated Normalized Difference Vegetation Index (NDVI), monthly 1981.

Verbyla, D. (2001), A test of detecting spring leaf flush within the Alaska boreal forest using ERS-2 and Radarsat SAR data, *Int. J. Remote Sens.*, *22*, 1159–1165.

Vermote, E. F., N. El Saleous, and C. Justice (2002), Atmospheric correction of MODIS data in the visible to middle infrared: First results, *Remote Sens. Environ.*, *83*, 97–111.

Viereck, L., and E. Little (1972), Alaska trees and shrubs, in *Agriculture Handbook*, For. Serv., U.S. Dep. of Agric., Washington, D. C.

Walker, D., et al. (2003), Phytomass, LAI, and NDVI in northern Alaska: Relationships to summer warmth, soil pH, plant functional types, and extrapolation to the circumpolar Arctic, *J. Geophys. Res.*, *108*(D2), 8169, doi:10.1029/2001JD000986.

Weller, G., , P. Anderson, and B. Wang (Eds.) (1999), The potential consequences of climate variability and change in Alaska: A report for the U.S. global change research program, 40 pp., Cent. for Global Change and Arct. Res., Fairbanks, Alaska.

Western Regional Climate Center (2007), Fairbanks WSO airport monthly climate summary (1949–2005). (Available at http://www.wrcc.dri.edu/)

White, M. A., P. Thorton, and S. Running (1997), A continental phenology model for monitoring vegetation responses to interannual climatic variability, *Global Bioeochem. Cycles*, *11*, 217–234.

Wissman, V. (2000), Monitoring of seasonal thawing in Siberia with ERS scatterometer data, *IEEE Trans. Geosci. Remote Sens.*, *38*, 1804–1809.

Zhang, X., et al. (2003), Monitoring vegetation phenology using MODIS, *Remote Sens. Environ.*, *84*, 471–475.

Zhou, L., C. J. Tucker, R. K. Kaufman, D. Slaybeck, N. V. Shabanov, R. B. Myneni, and M. G. Taylor (2001), Variation in northern vegetation activity inferred from satellite data of vegetation index during 1981 to 1999, *J. Geophys. Res.*, *106*, 20,069–20,083.

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